SPATIAL AND TEMPORAL ONLINE CHARGING/DISCHARGING COORDINATION FOR MOBILE PEVS

MIAO WANG, MUHAMMAD ISMAIL, XUEMIN (SHERMAN) SHEN, ERCHIN SERPEDIN, AND KHALID QARAQE

ABSTRACT

Coordinated charging is an effective charging plan for PEVs to improve the overall system energy utilization and prevent the overload of an electric power grid. On the other hand, PEVs, which have energy storage and controllable loads, can be discharged to help the grid to smooth the fluctuations, for example, introduced by distributed generators (DGs). Either to prevent overloading or to regulate the power grid, most existing charging/discharging plans focus on temporal charging/discharging coordination for parked vehicles. However, for moving vehicles, spatial coordination can also bring benefits to the grid. For spatial coordination, the range anxiety problem should be carefully handled, since PEVs cannot reach some charging stations due to the limited battery levels. In this article, by exploiting both spatial and temporal coordinations, we introduce an online PEV charging/discharging strategy considering range anxieties. To collect real-time information for the proposed online strategy, a heterogeneous wireless infrastructure is proposed by integrating cellular networks with vehicular ad-hoc networks (VANETs). Challenging issues are discussed in terms of modeling PEV mobility, network selection for real-time information delivery, balancing the trade-off between the grid power utilization and drivers' preferences, and modeling business revenues for charging/discharging. Case studies demonstrate that joint spatial and temporal charging coordination can effectively improve power utilization and avoid overloading the power grid.

INTRODUCTION

Plug-in electric vehicles (PEVs), as a promising component of sustainable and eco-friendly transportation systems, have received considerable attention recently [1, 2]. Partially or fully refueled by electricity, PEVs have great potential to save thousands of dollars in gasoline costs over the vehicle's lifetime. For instance, a TESLA Model S, a pioneer retail battery PEV produced by TESLA Motors, costs only $30 per kilometer, while a gasoline-fueled premium sedan costs $173 per kilometer [3]. Besides, the adoption of PEVs into the transport sector can reduce the consumption of conventional energy sources (e.g. gasoline) and environmental pollution (e.g. greenhouse gas emissions). As reported in [1], battery powered PEVs, which completely depend on rechargeable batteries and thus produce no emissions, can reduce overall emissions from the transport sector by 70 percent. Therefore, it is expected that PEVs will account for a higher market share in the transport sector. According to the report of the Electric Power Research Institute (EPRI) [2], the PEV penetration level can reach 35 percent, 51 percent, and 62 percent by 2020, 2030, and 2050, respectively.

The widespread adoption of PEVs brings new potential benefits and challenges to the operation of the grid. On the challenges side, high PEV penetration levels will lead to overload charging problems for the smart grid. For example, electric taxi charging, which is very likely to coincide with the peak demand time of the power system, can lead to an overload of power consumption in a distribution feeder, resulting in power system instabilities in voltages and thus reduction in the energy supply [4]. This is especially true for fast PEV charging, as it requires much higher power than the regular charging. On the potential benefits side, PEVs with energy storage and controllable loads can be used to help the grid match fluctuating electricity generation, due to renewable sources, to the load demand and/or to charge other PEVs, leading to fewer requirements in terms of extra storage devices. Specifically, via the bidirectional charger, PEVs are capable of not only drawing energy from the power grid with the plug-in function (i.e. charging via grid-to-vehicle (G2V)), but also delivering the energy back to the grid (i.e. discharging through vehicle-to-grid (V2G)). Via V2G, discharging from the PEVs with extra energy can help regulate the frequency and voltage of the grid. Furthermore, through interac-

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tion among PEVs, an aggregator can perform a coordinated control of a group of PEVs for charging and discharging purposes, that is, energy can be transferred among PEVs in swapping stations [5], i.e. vehicle-to-vehicle (V2V) charging/discharging.

The above challenges, e.g. avoiding overload, and the potential benefits, e.g. regulating the frequency, can be better addressed (and exploited) through coordinated charging/discharging strategies. So far, the research has focused on temporal coordination, with most of the work distributing the charging/discharging decisions in the power system over different time periods. Temporal coordination is performed for a group of PEVs that are assumed to be ready for charging/discharging within a specific area (e.g. parking lots or residential areas). In practice, PEVs may need fast charging when moving on the road (e.g. electric taxis). In addition, mobile PEVs can contribute to a V2G or V2V transaction if high revenue is expected. Thus, better results can be achieved by combining the temporal information with the spatial coordination for mobile PEV charging/discharging.

In the spatial coordination of mobile PEVs, the charging/swapping station that is assigned for the PEV may be too far to reach given the PEV's current location and battery energy level (i.e. range anxiety, which presents tension between the PEV travel cost[1] and battery energy level), leading to the PEV battery being depleted on the way for G2V or resulting in less revenue for charging/discharging. Therefore, drivers prefer charging/swapping stations at locations with less travel cost or more charging/discharging revenue while considering range anxieties. However, such a preference may conflict with the system's technical constraints. Therefore, new online charging/discharging strategies are required to consider both drivers' preferences and system constraints.

To this end, in this article we focus on leveraging the real-time vehicle information for designing an efficient PEV online charging/discharging strategy based on both spatial and temporal coordination. Specifically, three underlying key problems will be investigated:

- What kind of information is required to support the spatially and temporally coordinated online charging/discharging strategy?
- How to efficiently and reliably obtain the real-time information for the PEV online charging/discharging strategy?
- How to design mobility-aware coordinated PEV charging/discharging?

We first review the related work in the next section and then propose solutions to those problems.

Classifications of Charging/Discharging Strategies

Several studies have indicated that the power system can be significantly affected by the high penetration levels of PEV charging [6]. In addition, coordinated discharging can bring great benefits to the grid. The research on charging/discharging strategy design for PEVs in the smart grid can be categorized from different perspectives as follows.

Centralized and decentralized strategies (e.g. [4]): For a centralized strategy, the charging/discharging strategy is operated based on a centralized structure. The global optimal performance can be quickly obtained, based on the high signaling overhead for information collection and high computation requirements. For a decentralized strategy, the decisions are locally made by the PEVs following an iteration-based approach through information exchange, with reduced computation complexity. Therefore, in this article we propose a decentralized coordination strategy.

Pure PEV coordination (e.g. [4]) and price control-based strategy (e.g. [7]): In pure PEV coordination, drivers are assumed to unconditionally follow coordination decisions. However, for mobile PEVs, such decisions impose a conflict between the system's technical limitations and driver preferences. Such a problem can be addressed through price control. Charging/discharging decisions are made based on electricity prices, which are jointly set by charging stations based on the total demands/supplies of PEVs' charging/discharging profiles. In this article we propose a strategy based on price control, by which a driver is motivated to follow the coordinated decision due to a cheaper electricity price for charging and higher revenue for discharging.

Myopic (e.g. [8]) and predictive (e.g. [9]) charging/discharging strategies: The myopic decisions of charging/discharging are based only on the current information in the grid, while in a predictive strategy, future power demands in the grid are considered when making charging/discharging decisions. Since myopic charging/discharging strategies do not consider the effects of the current and future PEV charging/discharging decisions on the power grid, the charging/discharging decisions through short-term prediction of power demands are more reliable in reality. Therefore, in this article we propose a predictive charging/discharging strategy.

Information for Spatial and Temporal Charging/Discharging Coordination Strategies

In this section we discuss the information needed to support the spatial and temporal charging/discharging coordination strategy. These include the information required by the stations and the PEVs.

Information Required by Charging/Swapping Stations

Since the coordinated electric prices are decided by charging/swapping stations when the collected PEV charging/discharging decisions are compared to the load capacities of charging/swapping stations, the information of the fluctuating load capacities at charging/swapping stations should be predicted. There exist not only temporal fluctuations in the load capacity of each distribution feeder but also spatial fluctuations in the load capacity among different distribution feeders at the same time.

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[1] In this article, the PEV energy consumed on the road to reach a charging/swapping station is referred to as the travel cost.

Time	Bus number	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}	B_{11}	B_{12}
21:00	P(MW)	TBD	4.0	5.5	—	6.0	5.5	4.5	—	3.5	TBD	3.0
	Q(MVar)	—	3.0	5.5	—	1.5	5.5	4.5	—	3.0	—	1.5

Table 1. Active and reactive power load values of buses at 21:00.

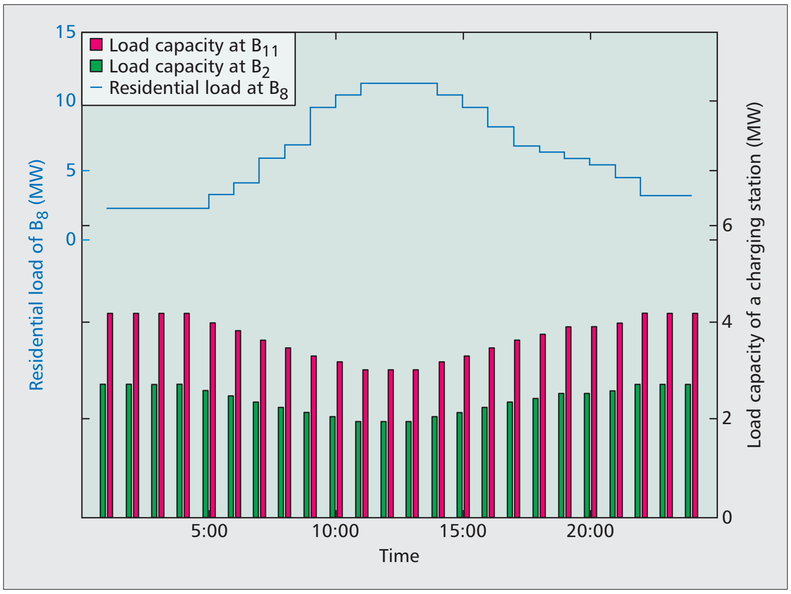

Figure 1. Load capacities of charging stations vary with both space and time.

Illustrative Example of Fluctuating Load Capacity — For simplicity, assume a power system without distributed generators (DGs) and consider the parameters of the 12-bus distribution system in [10] with the load demand enlarged to the MW level, as shown in Table 1. Two charging stations are connected to buses B_2 and B_{11}, respectively. The residential power load is loaded at bus B_8. The input voltage is set to 1.0 per unit (pu), and the minimum allowable voltage is 0.9 pu, with the impedance of any line section being $0.005 + j0.0046$. The normalized power loads at B_8 over that at 21:00 pm (Table 1) during a day are shown in Table 2, according to the trend in [11]. Suppose the other residential power load trends also change with time similarly to that of B_8.

Since the charging station capacity can be determined based on the predefined voltage limitations and sensitivity factor value for the additional load at each bus [4], the load capacities of the charging station buses (i.e. B_2 and B_{11}) can be determined as 2.6 MW and 4.0 MW at 21:00 pm, respectively.

Consider a PEV, e.g. a TESLA Model S sedan, with battery capacity of 85 kWh [3]. It imposes a maximum electrical load of 250 kW on the bus, when the charging period is set to 10 min (i.e. fast charging scenario) with a maximum charging energy of about 41 KWh. Suppose all PEVs have the same charging rate. Hence, at 21:00 pm the charging station connected to B_2 can accommodate 10 standard PEVs for simultaneous charging, which corresponds to a maximum additional load of 2.5 MW (=10*250 kW < 2.6 MW). Similarly, the PEV charging station located at B_{11} can accommodate 16 standard PEVs for simultaneous charging at 21:00 pm (=16*250 kW = 4 MW).

To demonstrate the temporal fluctuations, consider for example bus B_8. The power load of B_8 is shown in Fig. 1, according to the trend in Table 2. Since the residential power loads vary with time as shown in Fig. 1, the load capacities of charging stations, which can be obtained based on the power flow equations, also vary with time, accordingly. In other words, different charging stations at different locations can accommodate different numbers of PEVs over time and space. As a result, the load capacities of charging stations, which are fluctuating both spatially and temporally, are the required information for designing the strategy. Note that the historic remote terminal unit (RTU) readings of the power grid[2] can be utilized to provide such information. In addition, charging/swapping stations should receive information regarding the PEVs' charging/discharging decisions (i.e. power demands or power supplies). The gathered information, in terms of spatial and temporal load capacities and power demands, can be used for price updates.

Real-Time Information Required by PEVs

The charing/discharging decisions are made by individual PEVs while considering the travel cost and charging/discharging revenue. For spatial coordination of mobile PEVs, range anxiety is the key to the viability of charging/discharging decisions; otherwise, the batteries of PEVs will be depleted on the way to G2V operations, and less revenues will be achieved for V2V/V2G operations. Hence, new efficient PEV charging/discharging strategies must be designed to take care of real-time vehicle information (e.g. locations and current battery energy levels) in order to address the range anxiety problem and incorporate spatial coordination in the charging/discharging strategy.

Illustrative Example of PEV Range Anxiety — Consider a Tesla Model S [3] with a range of 480 km; its lithium-ion battery pack stores 85 kWh. The energy-consumption of this PEV is 18 kWh per 100 km. On the other hand, the penetration of the deployment of PEV charging stations would be a slow process [3], most likely leading to a sparse distribution of charging stations. The deployed charging stations in the Kitchener-Waterloo region[3] are shown in Fig. 2. There are three charging stations in Waterloo, and two in Kitchener. When the power demands of both charging stations in Kitchener are much higher than those in Waterloo, PEVs in Kitchener can be dispatched to the charging stations

[2] An RTU is a microprocessor-controlled electronic device that interfaces objects in the physical world to a distributed control system or SCADA (supervisory control and data acquisition) system by transmitting telemetry data to a master system, and by using messages from the master supervisory system to control connected objects.

[3] Charging station locations can be found online: http://www.caa.ca/evstations/.

Time	1am	2am	3am	4am	5am	6am	7am	8am	9am	10am	11am	12pm
Normalized power	0.5	0.5	0.5	0.5	0.7	0.9	1.3	1.5	2.1	2.3	2.5	2.5
Time	1pm	2pm	3pm	4pm	5pm	6pm	7pm	8pm	9pm	10pm	11pm	12am
Normalized power	2.5	2.3	2.1	1.8	1.5	1.4	1.3	1.2	1.0	0.7	0.7	0.7

Table 2. Normalized residential power load at B_8 over the power load at 21:00 (Table 1) during a day.

in Waterloo. Without considering the range anxieties, the batteries of some PEVs will be depleted on the way to route to Waterloo. Hence, based on both load capacities of the power grid and individual real-time vehicle information (e.g. locations and battery energy levels), PEVs can make charging/discharging decisions. Then, the decisions can be addressed in a predictive fashion:

- Whether a vehicle should be charged/discharged in the next period based on the current battery energy level?
- Which charging/swapping station should an individual vehicle be directed to considering the range anxiety based on the vehicle current location, while protecting the charging feeders from an overload situation for a G2V operation and achieving high revenues for a V2V/V2G operation?
- How much energy should be charged/discharged to (from) this vehicle in the next period so as to improve system energy utilization and guarantee power system stability?

In the next section we provide the solution to efficiently and reliably obtain the real-time information for the PEV online charging/discharging strategy.

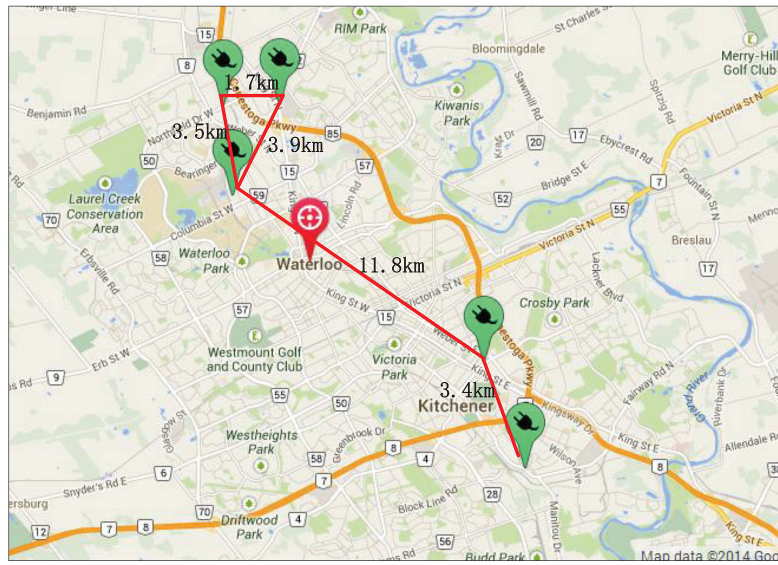

Figure 2. Locations of the existing charging stations in K-W region.

Heterogeneous Wireless Network-Enhanced Smart Grid

To efficiently and reliably deliver real-time information for the PEV online charging/discharging strategy, a heterogeneous wireless network is first introduced. Then we show the heterogeneous wireless network-enhanced smart grid architecture, aiming at supporting the proposed charging/discharging strategy for PEVs based on both spatial and temporal coordinations.

Heterogeneous Wireless Networks

To deliver the information required by a charging/discharging strategy in a real-time manner, most of the existing works rely on cellular networks [7] (e.g. GSM, 3G, LTE, and so on [12]). The advantage of a cellular network is obvious due to the large coverage of a base station (BS). However, inevitable drawbacks of cellular networks limit their practicability in the collection of vehicle information. As cellular systems are not designed for vehicular data collection, the data collection services can incur high costs. In addition, the high volume of vehicular data may cause congestion of other cellular services, especially when the vehicle density is high.

Vehicular ad-hoc networks (VANETs) have recently emerged as a promising technology for providing revolutionized broadband services to vehicles. By deploying wireless gateways (e.g. road-side units (RSUs)) along highways/sidewalks and equipping vehicles with on-board communication facilities (e.g. on-board units (OBUs)), two communication modes are enabled for vehicles on the move: vehicle-to-RSU (V2R) communications and vehicle-to-vehicle (V2V) communications.[4] Exclusively designed for information exchange among highly mobile vehicles and RSUs in a multi-hop fashion, VANETs can deliver the required real-time information efficiently via short-range V2V and V2R communications. As a result, large-volume vehicle information collection is made cheaper than if handled via cellular networks. However, VANETs suffer from intermittent connections among vehicles and RSUs due to the short-range V2V and V2R communications, leading to possible transmission delay for real-time message delivery. The transmission delay can affect the PEV charging/discharging decision, since the moving PEV will keep consuming energy while waiting for the decision, that is, introducing an additional travel cost incurred by transmission delay.

By integrating both cellular networks and VANETs in the heterogeneous wireless medium, more efficient methods for message delivery can be obtained with a low-cost communication network solution, e.g. in terms of low deployment and operation costs. Therefore, we use a heterogeneous wireless network to deliver messages for the online charging/discharging strategy design.

[4] Note that, in this article, the term V2V is used in two different contexts, one for VANET communications among vehicles and the other for energy transfer among PEVs.

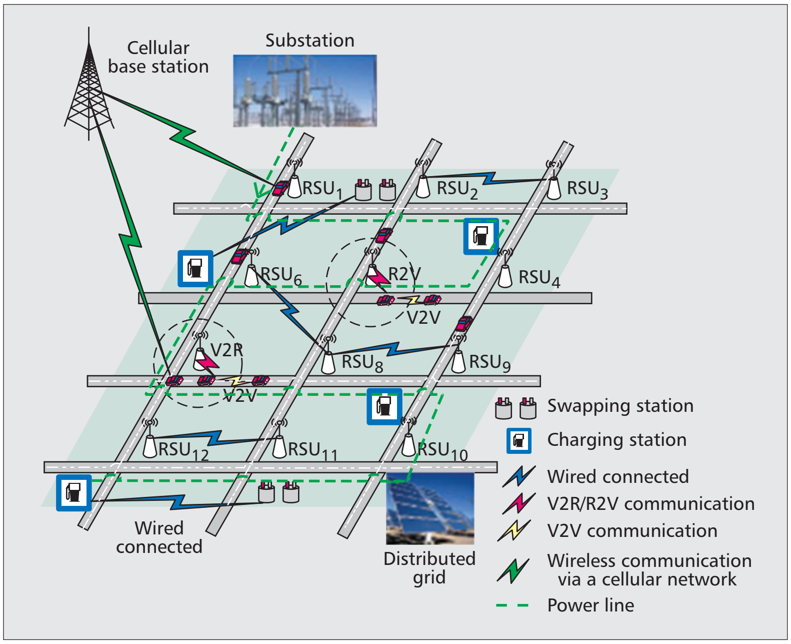

Figure 3. Heterogeneous wireless network-enhanced smart grid.

Heterogeneous Wireless Network-Enhanced Smart Grid Architecture

Figure 3 shows the proposed heterogeneous wireless network-enhanced smart grid architecture, consisting of a power distribution system with DGs, charging stations, swapping stations, PEVs, access points (i.e. RSUs) along the roads, and BSs of cellular networks.

The power distribution system includes a substation and a set of DGs supplying energy to the whole network through power feeders (i.e. buses). Charging stations located at different buses provide fast charging for all PEVs (i.e. charging via G2V). PEVs can also send electricity back to the grid at charging stations, that is, discharging through V2G. In addition, PEVs can exchange energy at swapping stations, that is, charging/discharging via V2V.

Time is partitioned into periods with equal duration τ. At the beginning of every period, price decisions are made based on the collected PEV decisions compared to the load capacities. Similarly, based on the collected PEV decisions, the maximal power that is exchanged at swapping stations (i.e. the load-capacity of the swapping station) can also be predicted in advance. In the following context, denote Bus j as B_j and the load-capacity for the charging/swapping station at B_j as C_j.

A set of RSUs, denoted as $\mathbb{R}$, is deployed along the roads for collecting the PEV charging/discharging information (i.e. individual charging/discharging decisions of PEVs) through V2R transmissions. Cellular network BSs are also deployed in the network to support wireless communications between BSs and portable transceivers in PEVs. Connected through wires to the charging stations, RSUs and BSs can relay the collected PEV decisions to the charging stations for updating prices to balance the load capacities and load demands. Thereafter, when the RSUs (BSs) obtain the updated prices from the charging/swapping stations, they relay the updated price signal to the PEVs through R2V and V2V transmissions (or via the cellular network).

Consider a set of mobile PEVs, denoted as $\mathbb{V}$. PEVs may need to be charged/discharged when moving on their way. Two network interfaces (i.e. cellular networks and VANETs) are integrated on a PEV, and based on relevant metrics, the real-time PEV information can be either exchanged among the on-board units (OBUs) through multi-hop V2V relaying or delivered to a cellular network BS through the equipped portable transceivers. Based on the received control signal, e.g. price control signal, charging/discharging decisions are made while considering the PEV range anxiety. The charging/discharging decisions include a charging/discharging load/rate of PEV υ at bus B_j in period k (denoted as $P_{\upsilon,j,k}$) and a charging/discharging indicator of vehicle υ indicating whether PEV υ will be charged/discharged at the charging/swapping station at bus B_j in period k, which is denoted as $x_{\upsilon,j,k}$. The charging/discharging decision $x_{\upsilon,j,k}$ is set to 1 when PEV υ is charged/discharged at B_j in period k, otherwise it is 0. Note that if PEV υ is decided to be charged, the charging load $P_{\upsilon,j,k}$ is positive; otherwise, when PEV υ is decided to be discharged, the charging load $P_{\upsilon,j,k}$ is negative. The PEV charging/discharging decisions are in turn delivered to charging/swapping stations via the specified wireless network.

In the next section we propose the mobility-aware coordinated PEV charging/discharging strategy.

Proposed Online PEV Charging/Discharging Coordination Strategy

In this section we first propose the PEV online charging/discharging coordination strategy based on price control. Then the technical constraints and challenging issues of the PEV charging/discharging coordination strategy are discussed.

The Predictive Decentralized Strategy Based on Price Control

In spatial coordination, the concept of range anxiety is introduced as a trade-off factor between the PEV travel cost and battery energy level. In the decentralized charging/discharging strategy, PEVs iteratively update their decisions while considering both range anxiety and electricity price in each iteration, so as to balance the travel cost and charging/discharging revenue, as shown in Fig. 4. The price control signal (with the updated prices) are provided by the charging stations (or swapping stations) to the PEVs via a wireless communication network. Specifically, in each iteration, charging stations jointly update their electricity prices, based on both the collected PEV charging decisions (i.e. power demands) in the last iteration and the predicted load capacities of charging stations (i.e. power supplies), to avoid charging station overload. Based on the received updated electricity prices, PEVs will update their charging/discharging decisions while considering the range anxieties to obtain more charging/discharging revenues. Therefore, the proposed strategy requires information exchange, over a number of iterations, among charging stations and PEVs in terms of power demands and electricity price. Hence, an efficient but economical wireless communication network is required to support such an online charging/discharging strategy. In summary, the proposed decentralized charging/discharging strategy operates iteratively. Each iteration contains two stages.

Price Update at the Charging/Swapping Stations: To balance the power demands and power supplies of charging/swapping stations, the electricity prices are updated based on the collected information, to avoid power system overload. The collected information is of two categories: the historic RTU readings of each bus from the power system through the wired connections, and PEV decentralized charging/discharging decisions. The former is delivered to the charging/swapping station through a wired connection, based on which the charging load capacity constraints of charging/swapping stations for G2V/V2G can be predicted. The latter is collected via the heterogenous wireless network (either through VANETs or cellular networks), based on which the power demands of charging/swapping stations can be estimated. The updated prices are delivered to PEVs via the heterogeneous wireless network.

Decision Making of the Predictive Coordinated PEV Charging/Discharging: PEVs fuse the electricity prices to calculate the optimal PEV charging/discharging decisions by considering the range anxieties and the charging/discharging revenues. The PEV charging/discharging decisions include both the charging/discharging rate, $P_{v,j,k}$, and the charging/discharging indicator, $x_{v,j,k}$. The decisions are in turn delivered to charging/swapping stations for price updating through the heterogenous wireless network in the next iteration.

After a charging/discharging decision is made for a PEV after a number of iterations, the decision is made available to the PEV GPS device, which will navigate the PEV to the chosen charging/swapping station. Also, both charging and swapping stations will receive information on the amount of power that the PEV will be charged/discharged, via the heterogeneous wireless network.

Technical Constraints of PEV Charging/Discharging Coordination Strategy

In order to implement charging/discharging control for PEVs in the smart grid, the power constraints on the feeders are first captured, followed by the charging/discharging constraints for mobile PEVs. Next, the design principles underlying the strategy are presented.

Power System Technical Constraints — Consider a smart grid that assumes the system model shown in Fig. 3. The power system can be abstracted as a one-line diagram with multiple buses. For further illustration, an example of a 12-bus system is depicted in Fig. 5. Let $\mathcal{B}$ denote the set of buses in the system, with a population of 12 buses in this example. The *generation buses* are defined as the buses injecting power into the system, that is,

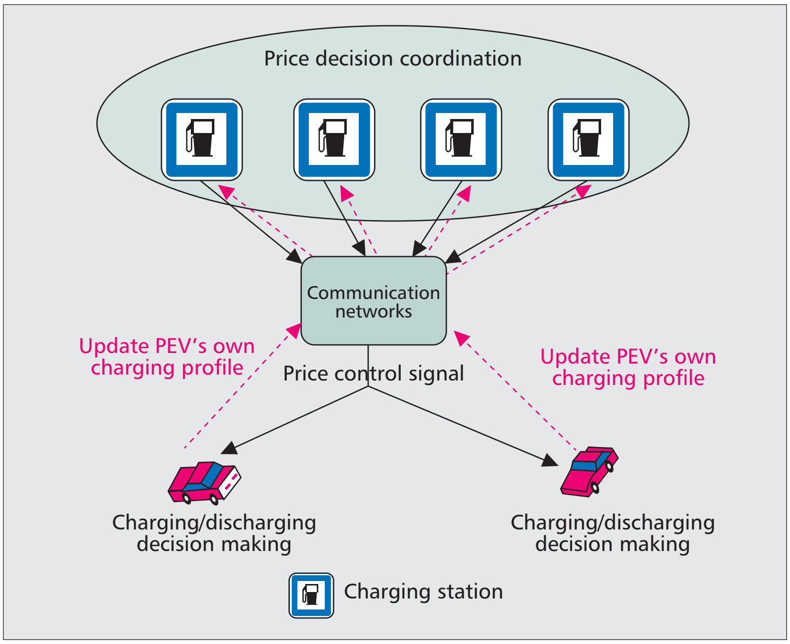

Figure 4. Distributed PEV charging/discharging strategy by price control.

B_1 and B_{10} in Fig. 5, while the other buses which only have loads are denoted as the *load buses*, that is, B_3, B_6, and so on. The power system is supplied through both the substation at the generation bus (i.e. B_1) and DGs (e.g. at B_{10}). PEV charging stations are located in the network at load buses, e.g. B_3, B_6, B_9, and B_{12}, respectively. Consider that each charging station connected to the grid is capable of supporting both V2G and G2V. In addition, the swapping stations are located at B_2 and B_{11} for V2V, as shown in Fig. 5.

Power System Constraints for Charging — For G2V, due to the thermal limit of the service cable or the current rating of the fuse, a PEV charging station at B_j is subject to a load-capacity constraint C_j, which can be calculated via the RTU readings based on power flow equations. In addition, the voltage limits and thermal limits of the feeders for charging should also hold, for example, within a range $[V_{\min}, V_{\max}]$ [13]. For V2V, the charging load-capacity at the swapping stations is limited by the available maximum power from PEVs, which can be predicted based on the collected vehicle information.

Power System Constraints for Discharging — For V2G, the discharging load-capacity is limited by the current carrying capacity of wires and other circuitry connecting PEVs to the grid [14]. For V2V, the basic power constraint is due to the power balance equations among PEVs, that is, at an aggregator, the total charging power should be balanced with the total discharging power.

Charging/Discharging Constraints for Mobile PEVs — For individual vehicles, the charging/discharging constraints for PEVs will be next evaluated by considering the travel cost due to PEV mobility.

When a mobile PEV is to be charged/discharged, the charging/discharging load of PEV υ ($\in \mathbb{V}$) at B_j in period k, that is, $P_{\upsilon,j,k}$, should be

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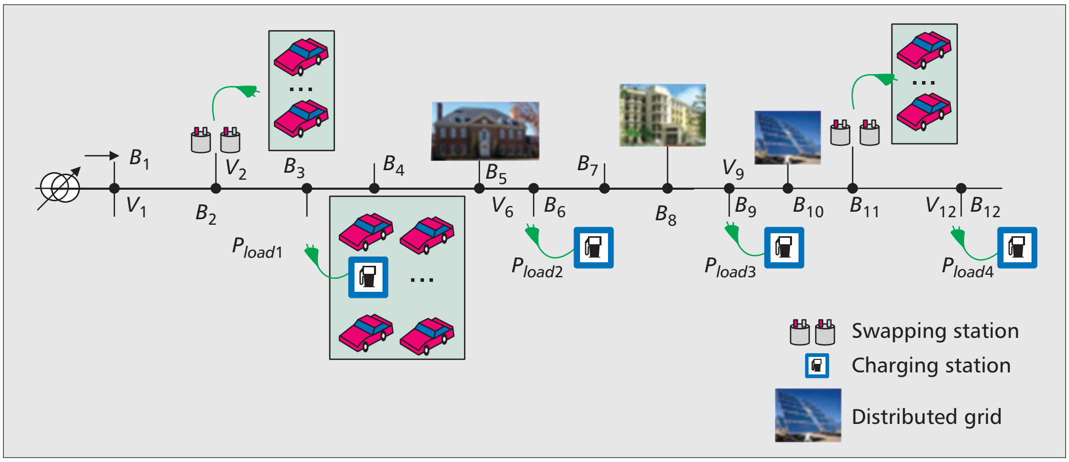

Figure 5. A power system model.

less than a certain charging load limit, $P^{\max}_{\upsilon,j,k}$, due to the PEV charger output power constraint. If PEV υ is not planned to be charged/discharged in period k, that is, $x_{\upsilon,j,k} = 0$, the charging/discharging load of PEV υ in period k should be 0.

Moreover, for PEV υ, during a single period only one charging/swapping station is selected, since a PEV can only be routed to one charging/swapping station at a time. In addition, during a charging/discharging period, the charging/discharging energy of each PEV should be limited by its battery-capacity (or a user predefined capacity) U, and the battery should not get depleted on the way and fail to be charged/discharged, that is,

$$0 \le P^{init}_{\upsilon,k} + \left(\sum_j a \cdot P_{\upsilon,j,k} - P^{\upsilon,k}_{cost} - P^{k}_{cons} \cdot \left(1 - \sum_j x_{\upsilon,j,k} \right) \right) \le U, \quad \forall k, \ \forall \upsilon \tag{1}$$

where $P^{init}_{\upsilon,k}$ is the initial energy stored in PEV υ in period k, $P^{\upsilon,k}_{cost}$ is the travel cost for charging/discharging in period k for PEV υ, and $P^{\upsilon,k}_{cost}$ should be less than the current stored energy, $P^{init}_{\upsilon,k}$; otherwise, the battery will be depleted before the PEV reaches the destination. Note that $P^{init}_{\upsilon,k}$ can be collected in real time by RSUs either based on V2V and V2R communications or through the cellular network. Let P^{k}_{cons} be the non-charging/discharging energy cost of each PEV for moving on the road if the PEV is not charged/discharged in period k. The cost P^{k}_{cons} can be determined by the drivers' preferences. The charging/discharging duration of each period is a hours. For instance, if we consider a 30-minute charging/discharging duration for each period, we have $a = 0.5$. Then, for a PEV charging/swapping station at B_j, the summation of all such PEV loads, $P_{j,k}$, in period k should be less than the aforementioned load-capacity of the bus, that is, C_j.

Design Principles of Charging/Discharging Strategy — The spatial and temporal PEV charging/discharging strategy in the heterogeneous wireless network-enhanced smart grid operates according to the following principles:

- At each charging station:
  – For G2V, due to the voltage and thermal limits of the service feeder, the summation of all PEV charging powers at this feeder should be held by the load-capacity of the charging station.
  – For V2G, the power constraint of PEV discharging powers is limited by the current carrying capacity of the PEV circuits.
- For V2V at swapping stations, the power balance equations among PEVs should be satisfied at the aggregator.
- For each PEV, the charging/discharging rate should be limited by the PEV charger output (input) power constraint.
- A PEV can be dispatched to at most one charging/swapping station at a time.
- The charging/discharging energy of each PEV should be limited by its own battery-capacity or driver target limit.
- The assigned charging/swapping stations must be within the range of individual mobile PEVs by taking into account the current locations and battery energy levels, considering the consumed energy to drive to the charging/swapping station and while waiting for the charging/discharging decision due to the transmission delay over the heterogeneous wireless network.

Challenging Issues

In order to efficiently deploy such design principles, there exist many challenging issues including PEV mobility modeling, selecting the transmission network, balancing the trade-off between the power system technical limitations and customers' preferences, and the business revenue model for V2G and V2V transactions.

Mobility Modeling of PEVs — The mobility model of PEVs has a direct impact on the travel cost to a charging/swapping station and hence affects the PEV charging/discharging coordination decision. Consider that PEVs are on the roads in the suburban area according to a mobility model, for example, Wiedemann 74 [15]. The mobility of each PEV can be characterized by random variables (S, λ). The vehicle velocity is represented by S, which takes n possible values. When $n = 2$, S has two states: a lower velocity S_L and a higher velocity S_H, and the velocity transition is modeled as a two-state continuous Markov chain with state transition rates, λ_{LH} or λ_{HL}, respectively. The model can be exploited to describe the realistic driving behaviors of people, that is, a driver drives at a velocity for a period and then changes to a higher/lower velocity based on his/her will, road conditions, or the headway distance between the vehicle and the one in front. Based on the n-state continuous Markov chain of the Wiedemann 74 model, the headway distance between PEVs, inter-contact time among PEVs, and vehicle-density, and so on, can be modeled, and therefore both the travel cost and the energy consumed due to the transmission delay can be calculated. Based on the PEV mobility model and by calculating both the travel cost and transmission delay, the range anxiety can be specified.

Network Selection for Real-Time Information Delivery — In VANETs, the PEV mobility results in intermittent V2V and V2R connections, which introduce a transmission delay and thus incur an additional travel distance (cost) while PEV υ is waiting to receive the decision via VANETs. On the other hand, using the cellular network for information delivery might incur additional monetary cost. The network selection mechanism can be designed to balance a trade-off between the travel cost due to transmission delay in VANETs and the monetary cost mainly due to cellular networks.

The travel distance while waiting to receive a decision through VANETs is denoted as $d_{\upsilon,k}$ for PEV υ in period k. Based on the mobility model of PEVs, the travel distance, $d_{\upsilon,k}$, during which PEV υ is moving and waiting for the charging/discharging decision in period k, can be calculated as $d_{\upsilon,k} = \psi(S, \lambda, \zeta, R, L, \pi)$, where $\psi(\cdot)$ is a function that measures the effects of transmission delay in VANETs on the travel distance $d_{\upsilon,k}$. The transmission delay in VANETs is decreasing with:

- The increased vehicle mobility parameters (i.e. S and $(1/\lambda)$, since increasing S and $(1/\lambda)$ can reduce the average number of hops in a multi-hop transmission link leading to a reduced transmission delay.
- The increased vehicle density (i.e. ζ) which may provide more chances to create a successful transmission link, and it might reduce the average transmission delay for a V2V/V2R communication.
- More possibilities for V2R transmissions in the network (i.e. by increasing transmission range R or deploying more RSUs to decrease the average distance between RSUs, L).
- A more efficient transmission mechanism π, for example, choosing the farthest node within the transmission range as the relay to reduce the number of transmission hops or designing an efficient distributed coordination function (DCF) in the medium access control (MAC) layer to avoid transmission collisions.

The travel cost due to the transmission delay in VANETs is denoted as a linear non-decreasing function $PC(d_{\upsilon,k})$ to measure the travel cost $P^{\upsilon,k}_{cost}$ for PEV υ to wait for receiving the decision in period k. By balancing the VANET travel cost $P^{\upsilon,k}_{cost}$ with the cellular network monetary cost, the wireless communication network can be employed for information delivery more efficiently and economically.

Balancing the Trade-Off Between the Power System Technical Limitations and Preferences of Customers — Due to the mobility of PEVs, drivers usually have their own preferences for choosing a charging/swapping station, for example, based on the shortest routing length or the most familiar station. The preferred charging/swapping station may not be able to support any additional power loads. Thus, based on the power system overload avoidance, another charging/swapping station can be assigned to PEV υ charging/discharging by spatial coordination.

Based on the travel distance $d_{\upsilon,k}$, the travel cost for PEV υ in period k in terms of energy, $PC(d_{\upsilon,k})$, should be no more than the charging/discharging revenue (e.g. a cheaper electricity price) to motivate drivers to route to that charging/swapping station. Similarly, the travel cost can also be formulated based on other driver preferences (for a subset of stations along the customer route). For example, given the customer route, he/she will prefer to choose a charging station along that route. The selected charging station should be chosen from a subset of charging station candidates only along that route. This subset of the charging station candidates can be incorporated into the optimization problem as an additional constraint.

Since drivers prefer to maximize their preferences for charging/discharging, there exists a trade-off between the optimal utilization of the power system and the customers' preferences. This trade-off unveils the challenging issues of how to define the preferences of individual drivers, and how to balance the trade-off between the system limitations and individual customers' preferences.

Business Revenue Model for Charging/Discharging — The spatial and temporal coordination introduces additional challenges for the bi-directional flow of electricity [16] (i.e. including both G2V and V2G). The business model established for PEVs interaction with the grid should benefit both customers and system operators. Specifically, the business model should provide an incentive for drivers to use the charging/swapping stations. Hence, the achieved revenue should be higher than the incurred travel cost. Moreover, the business model should balance power generation and demand for both PEVs and charging/ swapping stations, with a satisfactory revenue for the grid operator.

Case Studies of Spatial Charging Coordination

With the consideration of the aforementioned charging constraints and challenging issues, two case studies are presented to demonstrate the benefits of spatial and temporal charging coordination in terms of system power utilization, based on the same power data presented in Tables 1 and 2. Specifically, the first case study investigates the proposed strategy over different time periods of the day, with time varying total-available-charging-energy (TACE) (i.e. the total energy that can be supplied by the power grid to the charging stations while avoiding power overload at that time period). The second case study focuses on one

The selected charging station should be chosen from a subset of charging station candidates only along that route. This subset of the charging station candidates can be incorporated into the optimization problem as an additional constraint.

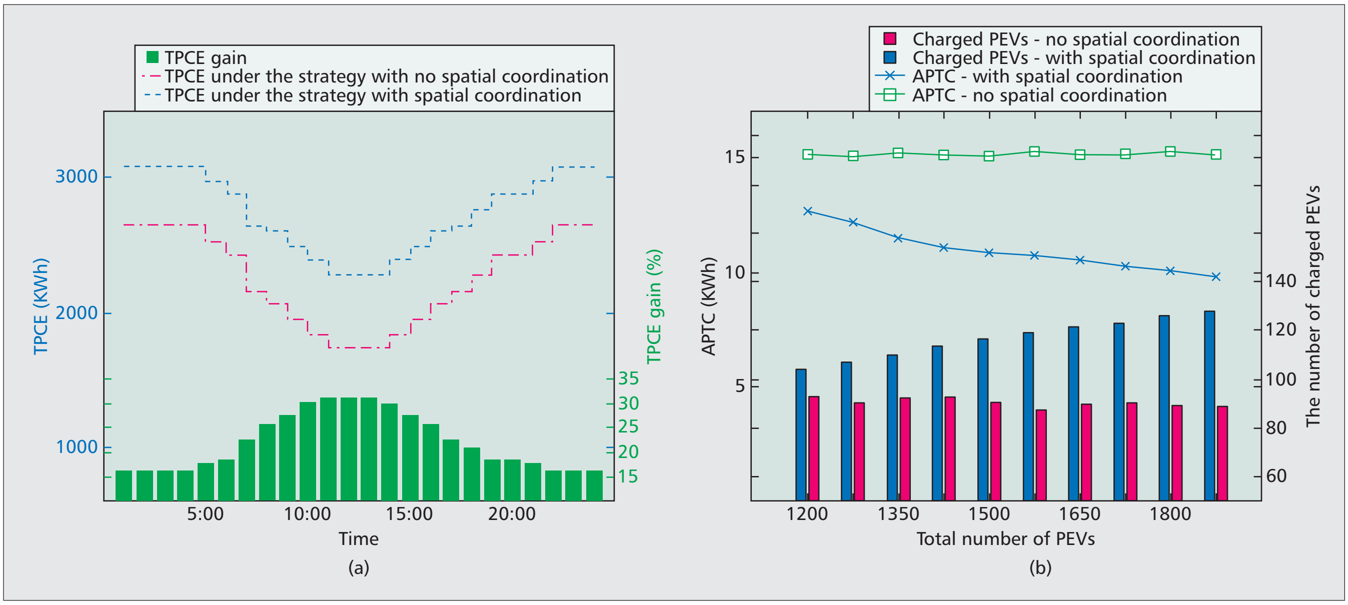

Figure 6. Comparison between the proposed strategy and the strategy without spatial coordination. a) TPCE under the strategy with/without spatial coordination; b) APTC and number of charged PEVs under the strategy with/without spatial coordination. TACE is fixed at 5400 KWh.

specific time period with fixed TACE. We compare the total charging energy of B_2 and B_{11} when considering spatial coordination to the one without spatial coordination. The performance metric is total-PEV-charging-energy (TPCE). It can be observed from Fig. 6a that over the day, the strategy that incorporates spatial coordination results in larger TPCE than the strategy in which charging decisions are made in the absence of spatial coordination. The TPCE gain under the strategy with spatial coordination is also shown in Fig. 6a.

On the other side, during a specific time period, when the total available-charging-energy (TACE) is fixed, with an increasing total number of PEVs, we compare the proposed coordinated strategy and the legacy strategy without spatial coordination, in terms of the average PEV travel cost (APTC) performance (i.e. the accumulated travel cost of all PEVs over the number of charged PEVs) as well as the number of successfully charged PEVs. As shown in Fig. 6b, it can be observed that when TACE is fixed, with a higher number of PEVs, the spatial coordination can balance the travel cost among demanding PEVs while avoiding the overload of charging stations, leading to a decreased APTC. As the APTC decreases, the average battery level for PEVs with charging requests when they arrive at the charging stations is higher due to a smaller travel cost to the charging station, resulting in a smaller average PEV charging energy. Thus, more PEVs can be charged at a fixed TACE. In the absence of spatial coordination, increasing the total number of PEVs may overload the power grid due to the high demand. To offload the high demand of a charging station, some PEVs have to route to a farther charging station for charging, leading to a higher average travel cost. However, due to range anxiety, some PEVs may fail to route to the farther charging station, leading to a smaller number of successfully charged PEVs compared with the spatial coordinated strategy.

Conclusions

In this article we have incorporated PEV mobility into the online charging/discharging coordination problems and proposed an online coordinated PEV charging/discharging strategy. Specifically, we have introduced an enhanced smart grid framework with the functionalities of real-time vehicle information collection through VANETs assisted by cellular networks. Based on the gathered real-time vehicle information, the mobility-aware coordinated PEV charging/discharging strategy can be performed jointly in a spatio-temporal framework to improve overall power utilization while avoiding the power system overload and generation-demand mismatch. Different challenges for developing such an online strategy have been discussed in terms of PEV mobility modeling, travel cost modeling, and balancing the trade-off between the power system technical limitations and customers' preferences. In addition, we have developed a business revenue model that provides incentives for drivers to participate in the V2G and V2V operations. In our future work we will consider more complicated charging/discharging scenarios, for example, DGs in the power grid, to further validate the benefits of the spatio-temporal coordinations in real-time practical applications.

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We have developed a business revenue model that provides incentives for drivers to participate in the V2G and V2V operations. In our future work, we will consider more complicated charging/discharging scenarios, for example, DGs in the power grid, to further validate the benefits of the spatio-temporal coordinations in real-time practical applications.